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Prediction of Chargeable Weight in Global Distribution Network Optimization

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Abstract. The aim of global distribution network optimization is to optimize the flow of goods between logistics nodes, leading to more efficient and compact packing. As a result, this optimization helps to reduce the shipping cost, which is calculated based on the weight and volume of package after cartonization. Shipping cost is calculated from chargeable weight. In this optimization problem, the routing or rerouting of products or raw materials would result in a new shipment network. To compare the performance of various shipment networks, we use the logistics cost of all shipments within a past time window as the evaluation criteria. Hence, when dealing with the routing/rerouting of numerous types of products/raw materials and having to consider numerous central distribution centers (CDC), a multitude of shipment network configurations would arise. The logistics cost for each routing/rerouting affects other networks and in turn, requires the logistics cost of all other shipment networks to be recomputed as well. Given the enormity of shipments in each network, it is infeasible to employ a cartonization solver to pack and then compute the chargeable weight of the shipments. Chargeable weight is the greater of actual weight and the volumetric weight of the carton after packing. In this paper, a neural network model is applied to predict the chargeable weight of shipments. Conventional machine learning models, such as random forest and support vector regression are used as the benchmark models. Moreover, to further reduce the overall mean error ratio, we propose using exact algorithm and Red Jasper's cartonization solver to calculate the chargeable weight for small shipments as this combined method runs fast and results in minimal error. As for large complex shipments, we propose using machine learning method to approximate the chargeable weight. Based on real data provided by one of the top five semiconductor equipment makers in the world for experimentation, results suggest that our method achieves a significant improvement in computational speed while maintaining a low mean error.

Keywords. Global distribution network design, Chargeable weight, Neural network, Cartonization

1. Introduction

The unprecedented disruptions over the past four years have undermined global integration and international economic systems. Geopolitics aside, the COVID pandemic alone revealed previously unnoticed vulnerabilities of international supply chains.

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Therefore, the twin priorities of cost and efficiency continue to be key concerns in the current context.

Indeed, to effectively manage global operational networks, suppliers of physical goods are confronted with a growing set of challenges. In 2021, the United States experienced a significant increase of 22.4% in commercial logistics costs, reaching a staggering $1.85 trillion. This figure accounted for approximately 8% of GDP. As for China, this figure reached $2.49 trillion in 2021, which accounted for 14.6% of GDP[2]. These costs primarily consist of expenditure related to logistics packaging, transportation, warehousing, and logistics management. Under such pressure, businesses must consider various cost and efficiency factors to optimize global production and distribution, enhance economic benefits, and gain competitive advantage.

The degree of supply chain management excellence of a corporation dealing in physical goods typically depends on the concerted efforts of four interrelated entities: suppliers, factories, distribution centers and markets, which are in turn, closely related and interact in traffic flows, information flows and capital flows[1-3]. Figure 1 illustrates the structure of a global production and distribution network. In terms of analyzing distribution networks, two aspects are primarily taken into consideration. The first aspect focuses on optimizing the flow of goods through the network based on existing facilities. The second aspect involves optimizing the facilities within the network.

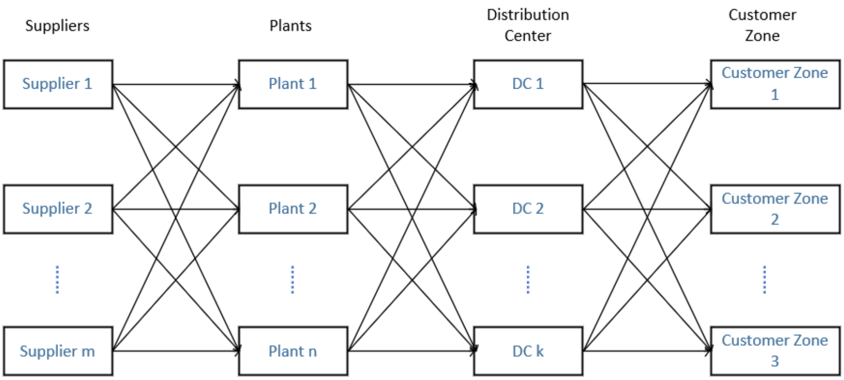

Figure 1. The Global Production and Distribution Network.

In this paper, the objective is to determine the optimal network redesign based on the configuration of available facilities, including their location, quantity, capacity, and other relevant factors[4]. Any corporation dealing in physical goods would pay close attention to network redesign, as it not only serves to improve customer service levels, but it could also substantially reduce supply chain management costs.

Optimal network redesign flow involves transporting rerouted goods to central distribution centers (CDCs) before delivering them to their respective demand locations around the world. This requires multinational corporations to establish CDCs worldwide. Corporations typically distribute their products through different CDCs, resulting in numerous potential distribution network structures to consider. To redesign an optimal network, the objective function is based on the transportation costs of past shipments over a specific time window. Routing or rerouting a type of product by changing its

[2] Full details of Logistics Report can be found at https://cscmp.org/CSCMP/Research/Reports_and_Surveys/State_of_Logistics_Report/CSCMP/Educate/State_of_Logistics_Report.aspx.

CDCs would result in changes to all shipments in those affected networks. In turn, these changes would also affect the chargeable weight of each shipment as service providers typically charge the maximum value of the actual weight and volumetric weight of a carton after packing (Figure 2)[5-6]. Therefore, the problem may also be viewed from the perspective of how to choose the appropriate CDCs for routing or rerouting products to minimize transportation costs.

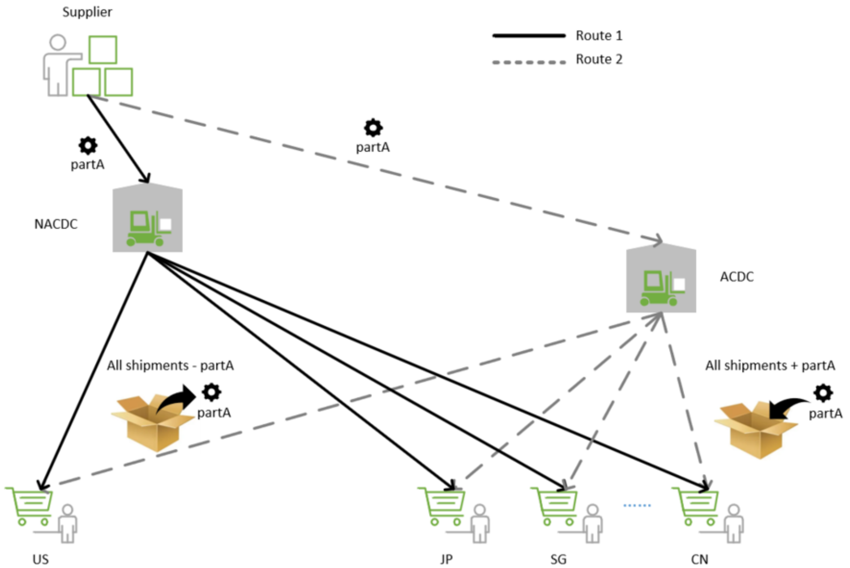

Figure 2. The Rerouting of Goods.

In logistics transportation, each shipment needs to be packed into cartons for transportation. The charge for each shipment is determined by the chargeable weight of cartons, shipping destination, the service level, and the logistics service provider. The chargeable weight is the maximum value of the actual weight and volumetric weight of the carton, and the volumetric weight is determined by the dimension of the cartons using a specific formula as follows:

$$volumetric\ \ weight(kg) = \frac{length(cm)\times width(cm)\times height(cm)}{5000} \tag{1}$$

Due to the high cost of air transportation, logistics companies use a denominator of 6000 for land transportation and 5000 for air transportation when calculating freight charges. However, the specific formula for calculating freight may vary depending on the logistics company [6]. The freight calculation process is shown in Figure 3.

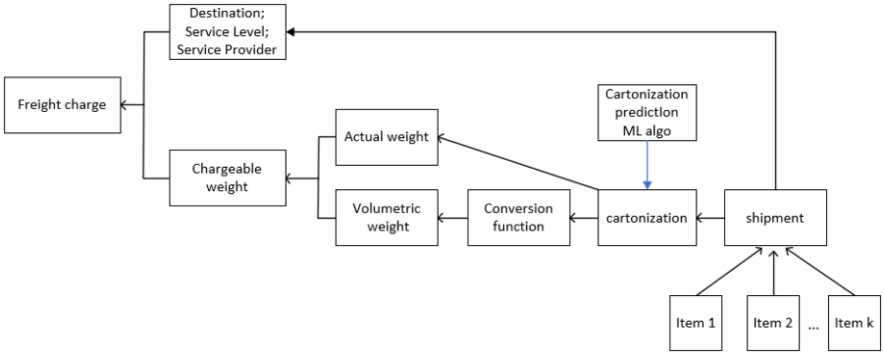

Figure 3. The Process of Calculating Charge of a Carton.

In the past, packing was mostly done based on the experience of workers. Indeed, manual packing is highly uncertain, and inexperienced workers often cause low utilization rate of carton space. In recent years, with the continuous development of computer technology and the application of new technologies such as artificial intelligence and the deployment of optimization algorithms in these new technologies, the efficiency of solving the 3D packing problem has been greatly improved. Currently, many researchers have developed various models and algorithms to solve the 3D packing problem. Meanwhile, commercial cartonization solvers such as the one developed by Red Jasper have emerged to solve 3D packing problems. Based on the data from one of their clients, and with the aid of Red Jasper's cartonization solver, the overall freight costs could be reduced by approximately 25%. Figure 4 is an example of the cartonization solver. Even when packing a complex case, space utilization of the cartons can reach more than 90%. For small quantities that require rerouting, cartonization solvers are efficient. But when it comes to the redesign of global distribution network, it becomes impractical to call the solver billions of times due to time constraint. Therefore, this article proposes the use of machine learning method to predict the chargeable weight of large complex shipments, offering a practical solution for calculating transportation costs in the redesign of global distribution networks.

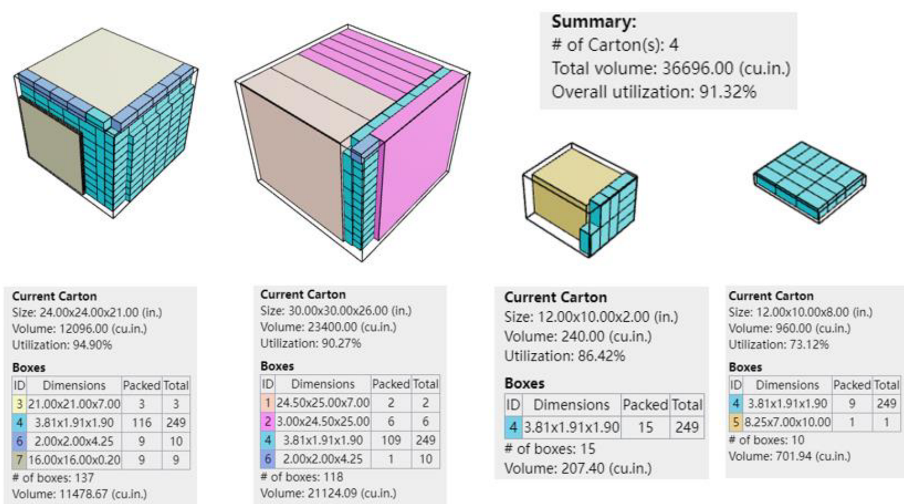

Figure 4. Red Jasper's cartonization solver.

This study makes two main contributions. Firstly, it explores a topic that has received little research attention so far. The existing literature on global distribution networks is primarily focused on the location, capacity, and opening cost of distribution facilities. This article addresses the long-overlooked issue of optimizing goods flow, which has been challenging due to the difficulty in evaluating the performance of potential distribution network structures. Therefore, we propose an objective function that uses the logistics costs of all shipments within a specific time window as the evaluation criteria. Additionally, we also present a method to predict the chargeable weight of shipments.

Secondly, we investigate the use of neural networks for predicting the chargeable weight of shipments. In our study, we also introduce two conventional machine learning algorithms, random forest (RF) and support vector regression (SVR) as the baseline models. However, relying solely on machine learning methods to predict the chargeable weight after packing may result in significant errors due to the complexity of the packing problem. Therefore, we divide the shipment data into batches. Exact algorithm and Red Jasper's cartonization solver are used for simple shipments when calculating chargeable weight, while machine learning methods are utilized for large complex shipments. This method has significantly reduced computation time compared to using the cartonization solver, while also achieving relatively low mean absolute percentage error.

For the remainder of this paper, we review the relevant literature in Section 2, describe the problem and the proposed method in Section 3, and introduce the dataset, training process of the model and the analysis of the results in Section 4. Finally, in Section 5, we provide a summary of the paper and discuss directions for future research.

2. Literature

2.1. Design of global production and distribution network

A systematic review of the existing literature on global production and distribution network design was conducted by Jan Olhager et al. to provide a reference for researchers and business managers who are interested in this research field, and to highlight future research works in this domain. The authors classified the literature according to the research methods deployed. Different research methods have different emphasis, but they are complementary. Finally, the authors put forward a research agenda for the design of global production and distribution networks [7].

In the review paper, most of the studies involved mathematical modeling methods. As well, most mathematical models aimed to minimize cost, but some models took delivery time, risk, and uncertainty into account. For instance, Geoffrion and Graves (1974) first proposed a mathematical model including the design of distribution networks between factories and customers. A multicommodity capacitated single-period version of this problem was formulated as a mixed integer linear program, and it was successfully applied to a large food company with 17 commodity types, 14 factories, 45 available distribution centers and 121 customer zones to find an optimal solution [8].

In another study, Ding et al. (2009) proposed a method combining multi-objective genetic algorithm (MOGA) and simulation, which not only aimed to optimize the structure of the distribution network, but also to optimize a series of operational decisions and control parameters carried out on it [2]. Moreover, the model not only considered cost factors in network design, but also includes customer service level, risk, and some uncertain factors. Different facility locations will lead to different network structures, this will lead to changes in the information flow and material flow of the network simulated in the model. Therefore, this method will regenerate the simulation model according to the selected network structure. In the model, each customer may automatically generate demand for multiple types of products and the number and frequency of this demand are generated randomly. At the same time, some rules will be set, such as demand fulfillment rules, order allocation rules, carrier loading and departure rules, and transportation allocation rules. Because there may be multiple links in two logistics nodes, two strategies are proposed in the allocation rules. The first is to determine a link to send the product according to the transportation cost and lead time, The second is to allocate the products to each link according to the allocation weight of the link.

Although we can also use the simulation method to measure the quality of a network, we use the cost in a past time window as the cost measurement of network quality to be aligned with the needs of the client. Regardless of the method, it is necessary to calculate the chargeable weight of the carton after shipment packing.

2.2. D-multiple bin size bin packing problem

During the global distribution of goods, it is necessary to transport goods to the distribution center rather than directly to the location of demand. Multiple goods will be packed before being shipped to the next node. For example, multiple goods are combined and packed into cartons for transportation to the central distribution center, where they are then split up, combined with other goods in the same way and shipped to the location of demand. In this process, all the packing of goods can be operated using the cartonization solver.

This problem is also called three-dimension Multiple Bin Size Bin Packing Problem (3D-MBSBPP), 3D-MBSBPP has special practical significance in warehouse management, transportation planning, container transshipment and other logistics issues. The problem is defined as: Given a set of three-dimensional rectangular boxes, each boxes is described as length l_i, width w_i, height h_i, quantity q_i, $i \in I$, and a set of three-dimensional rectangular bins, which can be described as length L_j width W_j, height H_j and cost C_j, $j \in J$. These boxes are highly heterogeneous, and the goal of 3D-MBSBPP is to pack these boxes orthogonally and without overlapping into a set of bins at the lowest cost. 3D-MBSBPP problem is a special case of 2D-MBSBPP, when $h_i = H_j$, $\forall i \in I$, $\forall j \in J$, 3D-MBSBPP is transformed into 2D-MBSBPP. Wascher G et al.(2007) pointed out in the classification of cutting and packing problems that MBSBPP is a generalization of the one-dimensional box packing problem (1BP), so MBSBPP is undoubtedly a strong NP problem [9-10].

The literature on the packing problem reports two main categories of solution methods: heuristic algorithms and reinforcement learning algorithms. Currently, there are numerous heuristic and metaheuristic algorithms available for solving single-container and multiple-container problems [10-16], and there are also many literatures on the method of reinforcement learning [17-20].

However, the current heuristic algorithms show better performance compared to reinforcement learning methods. In our research on network optimization problems, we utilized the cartonization solver developed by Red Jasper, which is based on the related works of Lim and Zhu [11, 12, 21-23] in this field. In their research, they proposed a block building approach for constructing packing. This method involves placing one block (consisting of multiple boxes) at a time until no more box can be loaded. Besides, the residual space selection strategy considers the anchor corner with the minimum Manhattan distance to its corresponding corner of the container, and employ a tree search method to search the best residual space-block pair. Considering the exceptional performance of this algorithm, we apply the cartonization solver for packing goods and design a global distribution network based on it. However, for large complex shipments, we employ machine learning method to predict the chargeable weight of the shipment packed by cartonization solver.

3. Problem description and method

3.1. Problem Description

The main goal of our study is to optimize the network redesign by quickly calculating the chargeable weight of a shipment, regardless of how complex the shipment data may be. A shipment, denoted as S_i, contains k (where k is at least 1) types of items, such as $item_1$, $item_2$, $item_3$ … $item_k$. Each item has its own length l_i, width w_i, height h_i, weight W_i and quantity q_i, where $1 \leq i \leq k$. In addition, the actual weight of the shipment after packing is known as W_{actual}. As the weight of the cartons can be negligible, W_{actual} is almost equal to the sum of the weight of all items. These features will serve as an important basis for predicting the chargeable weight of shipment. The cartons used for packing are pre-designed, which can reduce the total unused space of the cartons. Harsono (2019) provided a comprehensive analysis of the carton selection problem [24]. We conducted experiments using shipment data from one of the top five semiconductor equipment makers in the world over the past year. According to the data, there are over 40,000 types of parts. In Red Jasper's previous work with the semiconductor equipment maker, a set of 31 different dimensioned cartons were specifically designed for the equipment maker. The product dimensions and box dimensions are shown in Figure 5.

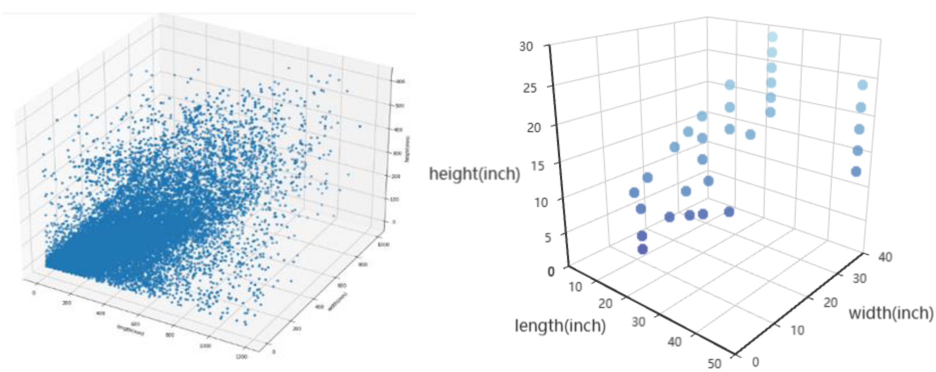

Figure 5. Products Size (Left) and Cartons Size (Right).

3.2. Method

Due to the complexity of the 3D-MBSBPP, which is an NP-hard problem, the chargeable weight calculation not only depends on the volumetric weight, but also depends on the total weight of the shipment and the cartons after packing. Predicting the chargeable weight of a shipment accurately through machine learning is a challenging task. As a solution, we propose a classification approach based on the quantity of items contained in each shipment. The reason we suggest this method is that in the actual shipment data over the past year, shipments containing only one or two items account for about half of all shipments. For these uncomplicated shipments, we can calculate their chargeable weight accurately and quickly using the exact algorithm. For single-item shipments, simply choose the smallest carton from the 31 pre-designed cartons that can accommodate the item efficiently. As for shipments with two items, we merge them into a simple block and then choose the smallest carton from the available cartons to pack the block. However, there is a possibility that packing these two items separately using smaller cartons might reduce total volume. These exceptional cases need to be considered.

Figure 6 below shows two examples of solutions using exact algorithm, indicating that this type of shipment is easily solvable.

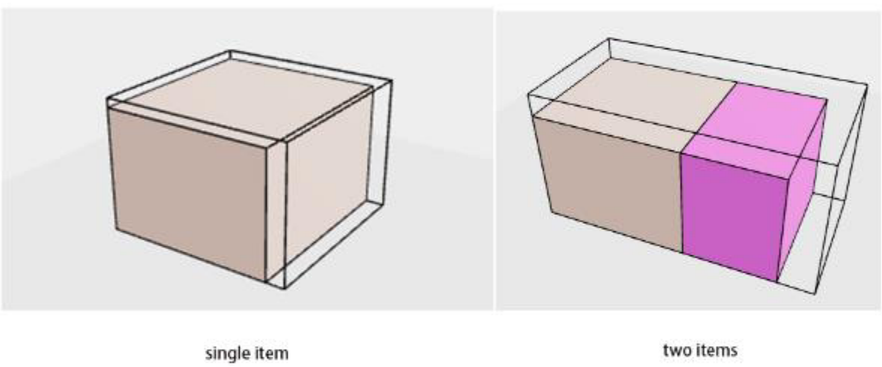

Figure 6. Two examples using exact algorithm.

That said, for some shipments, although the quantity of items may be more than two and are relatively simple, it is still hard to use exact algorithm to solve. In such cases, we turn to Red Jasper’s cartonization solver to calculate the chargeable weight. The cartonization solver is based on a heuristic search algorithm to solve the MBSBPP. Although the search process can be time-consuming for complex shipments, it is efficient for relatively simple shipments. Therefore, we need to determine the boundaries of complex and simple shipments. For complex shipments, using exact algorithms or cartonization solver would be time-consuming and impractical. As a result, we utilize machine learning methods to predict the chargeable weight of these shipments. Although there may be some errors in the predictions, they are negligible in the context of network design and the prediction speed are fast. We have explored various models for prediction but found that neural networks have the best performance. The overall strategy of the method is shown in Figure 7.

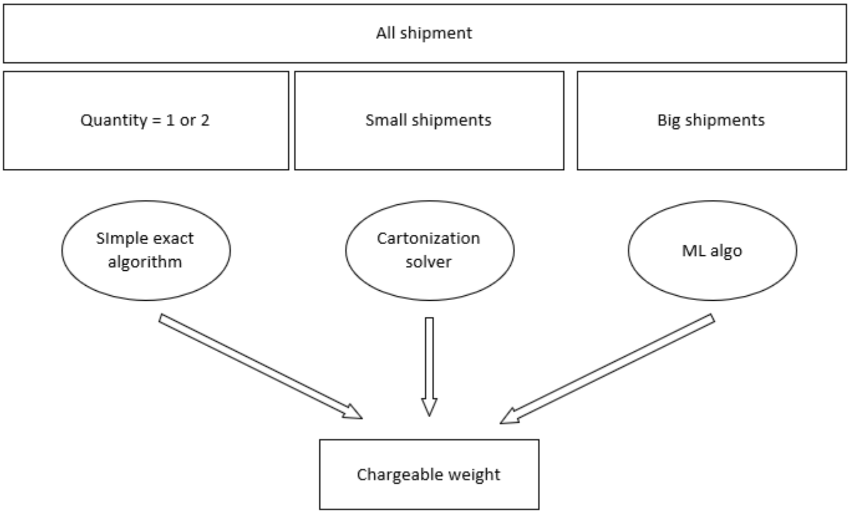

Figure 7. Overall Strategy.

In our experiment, we used a multilayer perception network with a two-dimensional input. The length of the first dimension corresponds to the number of item types. Since the number of item types in each shipment varies, the first dimension of the input data is variable for the neural network. The mathematical expression of the model is as follows:

$$h' = ReLu(item_i \cdot w_1 + b_1) \tag{2}$$

$$h'' = ReLu(h' \cdot w_2 + b_2) \tag{3}$$

$$h_i = ReLu(h'' \cdot w_3 + b_3) \tag{4}$$

$$h = \sum_{i=1}^{k} h_i \tag{5}$$

$$H = \{ h, \ W_{actual}, \ W_{volumn} \} \tag{6}$$

$$predict = Output(ReLu(H \cdot W_4 + \ b_4)) \tag{7}$$

$item_i$ is the vector composed of the length (l_i), width (w_i), height (h_i) and quantity (q_i) of an item in the shipment. $w_1, \ w_2, \ w_3, \ w_4, \ b_1, \ b_2, \ b_3, \ b_4$ are the weight and bias of four fully connected layers. Output is the full connection layer used to output the prediction results. In order to enable the model to learn complex relationships and prevent the vanishing gradient problem, we use Rectified Linear Unit (ReLu) as the activation function after all the full connection layers except for the output layer. The network input and structure are shown in Figure 8 below.

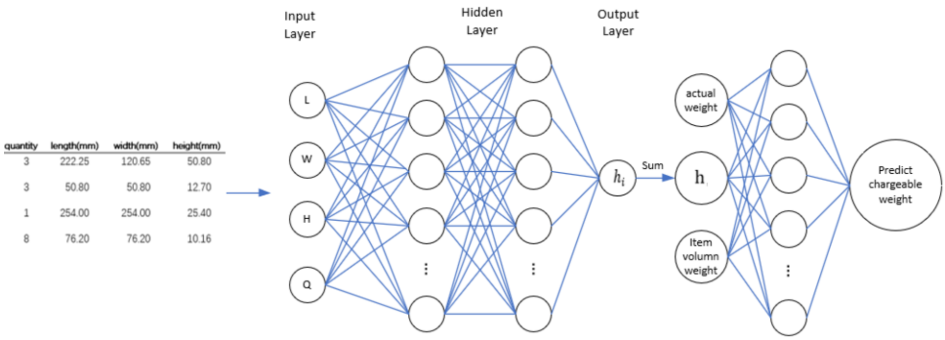

Figure 8. Network Structure.

Considering the overall loss function of the model, the difference between the expected output and the actual output is expressed by the following equation, where n is the batch size, which is set to 64 in training, w and b are the weight and bias of the network, which are the parameters we want to train, $y_{predict}$ and y_{truth} are the expected output of the model and the actual chargeable weight of the shipment.

$$loss(w, b) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_{predict} - y_{truth}}{y_{truth}}\right)^2 \quad (8)$$

4. Dataset, model training and result analysis

4.1. Dataset

As stated earlier, we utilize the actual shipment data from one of the top five semiconductor equipment makers in the world to conduct this experiment. This dataset is from 2021. After simple data processing, we obtained a dataset containing 66,972 shipment records. Among these records, 10,000 were randomly selected as the test set, while the remaining data was used as training validation set. The training validation set was then split into training and validation sets at a ratio of 0.2. We trained the model using the training data and evaluated its performance on the validation set.

4.2. Model training

During the training phase, we set the batch size to 64 and the learning rate to 0.02, which is halved every 30 epochs. We initialize the weight parameter of the model to a normal distribution with a standard deviation of 0.01 and set the bias parameter to 0. To prevent overfitting, we added a dropout layer to the model. In the validation phase, we use the ratio of error to actual chargeable weight as the evaluation metric and save the model parameters with the best performance during the validation process for later testing. The changes of the error during training and validation are shown in Figure 9.

$$absolute\ error = |y_{predict} - y_{truth}| \quad (9)$$

$$absolute\ percentage\ error\_ratio = \frac{error}{y_{truth}} \quad (10)$$

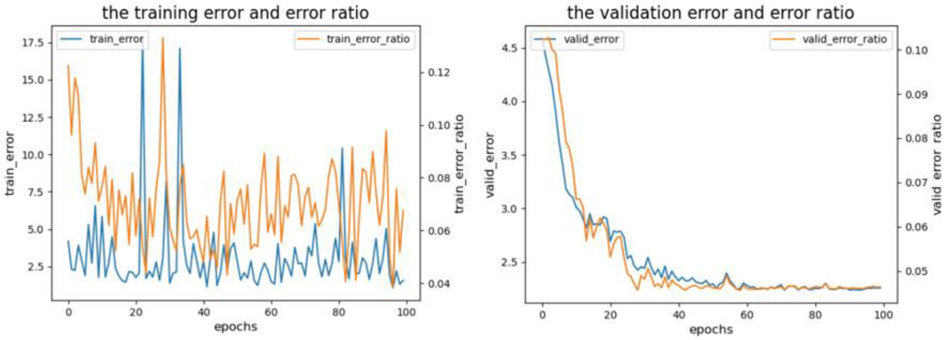

Figure 9. Training Process: The diagram on the Left is the Training MAE and MAPE, and the Diagram on the Right is the Validation MAE and MAPE.

At the same time, we utilized two conventional machine learning algorithms to compare with multi-layer perception method, namely random forest, and support vector regression. The two models are imported from the sklearn library with its default settings.

In the test phase, we used these models to predict the test set. The results are shown in Table 1. During the testing phase, we compared the results of three models. MLP model demonstrated significant advantages in multiple aspects. Firstly, our model exhibited better accuracy, which was validated by mean absolute error (MAE) 2.71 and mean absolute percentage error (MAPE) 5.83%, indicating more precise results. Secondly, although the solving efficiency of model solving efficiency was not as fast as the other two models, it showed a substantial improvement compared to traditional heuristic algorithms. Additionally, we can enhance solving efficiency by utilizing better hardware resources. However, the interpretability of the neural network model is somewhat challenging due to its complex structure and internal parameters, making it difficult to directly explain the specific reasons for model predictions.

Table 1. The comparison results of these three Models.

Models	MAE	MAPE	Time(s)
MLP	2.71	5.84%	17
RF	4.25	25.7%	10
SVR	4.71	18.6%	16

In order to further reduce the error to a lower level, we added an exact algorithm to the test. As illustrated in Figure 10, shipments with one or two items make up nearly half of all test shipments in terms of quantity. Therefore, using the exact algorithm to solve these shipments during testing can significantly decrease the mean error ratio. Moreover, the computation time of the exact algorithm is comparable to the prediction speed of the neural network. We also considered adding Red Jasper's cartonization solver to calculate the chargeable weight of the relatively simple shipments. We compared the total calculation error ratio and time of the test data by adjusting the boundaries between simple shipment and complex shipment. The training and testing of the model are carried out in the environment of RTX 3070.

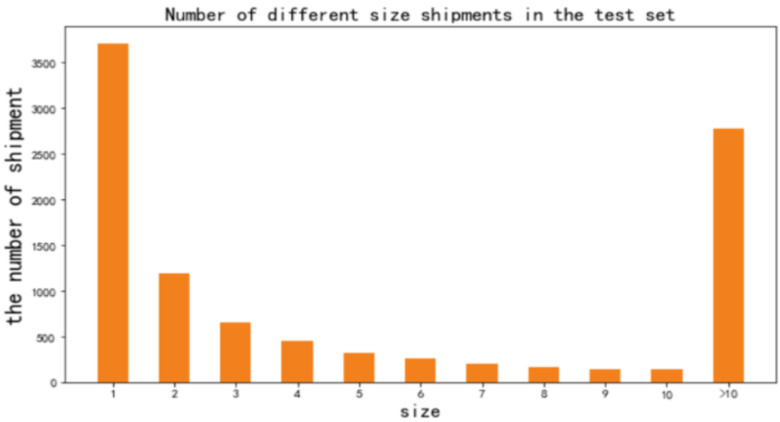

Figure 10. The number of different size shipment.

4.3. Results analysis

Table 2 presents the results of our experiments. We divide the test data into three batches for calculation. The first batch consists of shipments containing only one or two items, for which we used an exact algorithm to calculate the chargeable weight. Among these test data, there are 4,904 such shipments. Since these shipments are relatively simple, the calculation results obtained from the exact algorithm are comparable to those obtained by the cartonization solver, but the calculation time is only 6 seconds. The results of the second batch are generated using Red Jasper's cartonization solver to calculate the chargeable weight of the shipment. The error ratio for this batch is 0, which leads to a decrease in the overall mean error ratio, but the time is much longer than the other two batches. Therefore, it is necessary to strike a trade-off between time and error. The results of the third batch are generated using neural networks to predict the chargeable weight for complex shipments.

According to the experimental results in Table 2, for shipments with 4 or fewer items processed by the cartonization solver, the error ratio decreases quickly with a moderate increase in computation time. However, for shipments with 5 or more items, the opposite occurs. Therefore, it is advisable to limit the number of items processed by the cartonization solver to 4 or less, based on the network design scale.

Table 2. The MAPE and Time of Different Shipment Sizes Used for Cartonization.

The quantity of items processed by the cartonization solver in each shipment	MAPE and time for calculating chargeable weight using different method						Total MAPE and time	
	Exact algo		Cartonization		ML algo			
No shipments for cartonization	0%	6s	------	--------	8%	10s	4.1%	16s
quantity<=3	0%	6s	0%	11s	8.16%	10s	3.62%	27s
quantity<=4	0%	6s	0%	19s	8.15%	7s	3.25%	32s
quantity<=5	0%	6s	0%	28s	8.18%	6s	3%	40s
quantity<=6	0%	6s	0%	38s	8.23%	6s	2.8%	50s
quantity<=7	0%	6s	0%	56s	8.39%	5s	2.7%	67s
quantity<=8	0%	6s	0%	73s	8.42%	5s	2.56%	84s

Finally, for comparison, we use the cartonization solver to solve the packing of the shipment and calculate the chargeable weight for all test data, the performance on the test data is shown in Table 3. Our method is about 2,000 times faster than the cartonization solver with a mean absolute percentage error of only 3.25%.

Table 3. Comparison of ML Algorithm and Cartonization Solver.

The error ratio and time of different method	Mean error ratio	Time(s)
Cartonization Solver	0%	66859
The Method Combining ML, Exact Algorithm, And Cartonization Solver	3.25%	32

5. Conclusion

In this paper, we study the effects of machine learning methods on predicting the chargeable weight of shipments, using a popular network architecture MLP, and using conventional machine learning method RF and SVR as benchmark models for comparison. At the same time, we also propose to process the data in batches to reduce the overall mean error ratio.

By using machine learning methods to predict the chargeable weight of complex shipments and using exact algorithm and cartonization solver to calculate the chargeable weight of simple shipments, we improved the speed of calculating chargeable weight with low mean error ratio and provide a possible solution for cost calculation of rerouting networks in the context of global distribution network redesign. Through adjusting the boundaries between simple shipments and complex shipments, we achieved a trade-off between calculation accuracy and time. The three-batch method we used has a good performance on 10,000 test data, the calculation of the chargeable weight of all test data is completed within 15~30 seconds, and the average accuracy reaches 3% ~ 4%.

The findings indicates that the neural network model performs effectively in predicting chargeable weight of large complex shipments. Although the model considers the dimensions of items during the prediction phase, there may still be instances where the overall mean error ratio is affected. For example, for the shipment shown in Figure 11, the three dimensions of length, width, and height differ greatly, which can result in the fact that although the item is small, it must be packed in a large carton. In this case, we can make some adjustments outside the model, this is very helpful in reducing the overall error ratio.

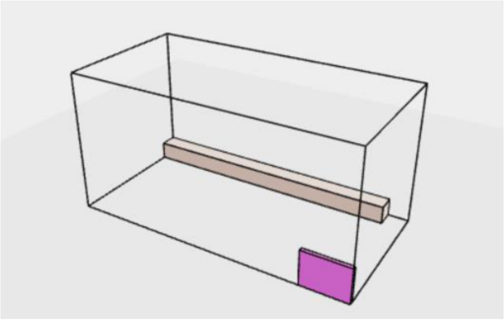

Figure 11. A Shipment with a Large Difference in the Dimensions of the Items.

Despite efforts to optimize this method, there are limitations. Some shipments may have inaccurate predictions due to significant variance. When the variance is too large, the large boxes tend to dominate the packing, then the other small boxes will not fill the remaining area. Although we have discussed methods to analyze the dimensions of the boxes to avoid such situations, there still exist certain exceptional case.

In the future, we intend to continue investigating the following two issues: 1) Following the work of this paper, which concerns the redesign of global distribution networks, we intend to work on rerouting specific parts manufactured by the factory and utilize the approach presented in this paper to calculate the total network cost, then optimize the distribution of these parts; 2) In order to avoid excessive calculation time for two-level optimization problems, we shall continue to investigate the use of machine learning methods to predict the results of meta- heuristic algorithms, which have significant research and application value in some problems that require high speed but allow certain errors.

With the continuous development of machine learning technology, we anticipate its widespread application in the field of optimization, particularly for large-scale, high-complexity and multi-level optimization tasks. Machine learning can be incorporated into heuristic or metaheuristic algorithms to help improve the execution speed and performance. For instance, machine learning can effectively reduce search space in heuristic algorithms by outputting promising areas in the global search space. Subsequently, a local search method is applied to further explore and improve the quality of solution. Furthermore, in the 3D-ODRPP problem, machine learning models can also learn from the given box information and give an approximate outer box size, then fine-tune it to obtain a high-quality solution.

In fact, this is a kind of “predict-then-optimize” thinking. This paradigm has profound implications in real-life scenarios. For instance, in vehicle route problem (VRP), uncertain travel times on roads due to varying traffic conditions, and fluctuating electricity demand in different regions during power grid scheduling create uncertainties in optimizing model parameters. However, by leveraging features like time and weather, we can predict these uncertain parameters and then proceed with decision optimization.

The superiority of machine learning should be more obvious. Traditional optimization algorithms usually require a lot of computing resources and time to solve large-scale and complex problems, while machine learning methods can improve efficiency through parallel processing and GPU acceleration, and can obtain high-quality solutions. Machine learning also has great research value in these problems, and we shall conduct in-depth research in this field, especially in supply chain optimization.

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